Designing a Conversational Travel Recommender System Based on Data-Driven Destination Characterization

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ABSTRACT

Recommending complex, intangible items in a domain with high consequences, such as destinations for traveling, requires additional care when deriving and confronting the users with recommendations. In order to address these challenges, we developed CityRec, a destination recommender that makes two contributions. The first is a data-driven approach to characterize cities according to the availability of venues and travel-related features, such as the climate and costs of travel. The second is a conversational recommender system with 180 destinations around the globe based on the data-driven characterization, which provides prospective travelers with inspiration for and information about their next trip. An online user study with 104 participants revealed that the proposed system has a significantly higher perceived accuracy compared to the baseline approach, however, at the cost of ease of use.

KEYWORDS

Tourism recommendation, Data mining, Cluster analysis, Conversational recommender systems

1 INTRODUCTION

In complex recommendation domains, such as the recommendation of tourist destinations, tweaking the algorithmic accuracy ad ultimo brings diminishing returns. It has been shown that the embedding of the algorithm in an adequate user interface is of similar importance [16]. Thus, in this paper, we present a data-driven conversational destination recommender system that has two contributions: it presents a novel, data-driven approach for characterizing destinations on user-understandable dimensions and shows how this characterization can be facilitated in a conversational recommender. This approach can be seen as an evolution of Burke's FindMe Approach [3] in the area of tourism. We thoroughly evaluated the system from the users' perspective to understand the effect of critiquing on the perceived accuracy of the recommendations and the satisfaction of the users from using the system.

After the literature review in the subsequent section, we will present the proposed method for characterizing destinations to realize content-based recommendations. Section 4, presents the the design and evaluation of the conversational recommender system that heavily relies on the previous characterization. We conclude our findings and point out future work in Section 5.

2 RELATED WORK

Tourism recommendation is inherently complex and has several facets. Borràs et al. enumerate four general functionalities of tourism recommender systems [2]: recommend travel destinations and tourist packs [17, 31], suggesting attractions [18], trip planners [10, 12], and social aspects [13]. In this paper, we focus on the first aspect and acknowledge that there are further definitions [1]. Herein, "destination" refers to cities. The challenge in recommending cities to a user at home arises from the intangibility of the items and the high emotional involvement [33]. It has been shown that leisure travel has a positive effect on an individual's happiness; however, it does not impact the overall life satisfaction, which has been attributed to poor tourism products [23]. An alternative conclusion could be that travelers visit the wrong places. This gives rise to researching improved destination recommender systems that can efficiently and effectively capture the user's preferences to overcome the cold start problem [5]. Given the characteristics of this domain, Burke and Ramezani suggested either the content-based [27] or the knowledge-based [3] paradigm [7].

In traditional information retrieval or static content-based recommendation, continuously querying for relevant items does not necessarily lead to better results [4]. Instead, a directed exploration of the search space using a conversational method is more promising [8, 11]. Burke et al. proposed and evaluated the FindMe approach [6], which allows the critiquing of single items so that the user can refine the recommendations iteratively until she is satisfied with the result. More advanced approaches on this topic are those of McCarthy et al., who propose a method to generate compound critiques [19], and McGinty and Smyth, who use the adaptive selection strategy to ensure diverse, yet fitting recommendations over the course of several critiquing cycles [21]. Recently, Xie et al. showed that incorporating the user experience into a critiquing system can improve the performance and recommendations at a reduced effort by the user [35]. In this study, we present a recommender system leveraging the potentials of the interplay between data science and user interface design. The items are characterized by a multidimensional space of features, which are intuitively understandable by the user and can then be critiqued in any direction. To overcome the problem of skeptical users hesitating to reveal their complete preferences [29] and the observation that users find it difficult to assess their exact preferences until when they are dealing with the actual set of offered options [26], the proposed method uses a mixture of explicit preference elicitation methods.

Using the content-based recommendation paradigm, one has to choose a domain model and distance metric to compute the most fitting items for the user. Such models can be realized through ontologies as done in SigTur [22] or in a the work of Grün et al. [14]. The latter is an example of ontologies being used to refine user profiles by enriching the generic preferences of a tourist through more specific interests. More often, items are simply characterized

Table 1: Raw values of exemplary cities

City	Venues	Arts	Food	Nightlife	Outdoors	Cost Index	Temperature	Precipitation
Rome	36,848	1,995	12,264	2,063	3,482	69.03	15.7°C	798mm
Mexico City	213,612	12,158	83,225	16,780	19,330	34.18	15.9°C	625mm
Cologne	16,163	966	4,107	1,144	2,127	67.36	10.1°C	774mm
Penang	50,647	2,193	21,389	1,686	5,273	43.98	25.7°C	1,329mm
Cordoba	3,636	246	1,282	427	379	55.11	17.8°C	612mm

using a multidimensional vector space model. In this case, the challenge is how to assign each item a value on each dimension, which is commonly done using expert knowledge. For instance, Herzog and Wörndl [15, 34] characterized regions using travel guides and their own expert knowledge. Neidhardt et al. developed the Seven Factor Model of tourist behavioral roles [24] based on the Big Five Factor Model [20] and a factor analysis of existing tourist roles [36]. Although they showed its merit in subsequent publications [25], a common drawback with approaches based on expert judgment is their scalability to large quantities of items and the dependency on the accuracy of human judgment. To overcome this, they proposed a strategy [32] for characterizing destinations within the Seven Factor Model. Using a huge data set of 16,950 destinations annotated with 26 motivational ratings and 12 geographical attributes, they proposed two competing methods, cluster analysis and regression analysis, to map the destinations to the vector space of the Seven Factor Model. In terms of destination characterization, this approach is the most similar to the one we proposed. The main difference is that our data model is directly defined via the data from the destinations and we are not dependent on expert ratings, which is an advantage when scaling the approach [9].

3 DESTINATION CHARACTERIZATION

The characterization of destinations such as regions or cities is a challenging task. What are the characteristics of a city for tourists to base their decision on whether to visit it or not? Previous approaches have relied on expert assessment [15, 32], but the shortcomings are a potential lack of objectivity and scalability as it is quite costly to rate myriads of destinations around the world. Thus, we propose a data-driven approach to characterize cities on the basis of the variety of venues per category. The underlying assumption is that, in a city with many restaurants, the travelers have plenty of options; thus, the quality of experience in the food category is high. Conversely, a city with very few cultural sites will be less interesting to a traveler that is interest in this topic. This section discusses how we collected data about venues and aggregated them to determine the touristic value of each city.

3.1 Collecting Venue Information

There are several providers of information about destinations. After performing a comparison of providers, such as Google Maps, Facebook Places, Yelp, OpenStreetMap, and some others, we decided to use the Foursquare Venue API[1], as it offers sufficient rate limitations and allows us to specify coordinates of a bounding box in the request parameters. The deciding argument for Foursquare was the detailed categorization of venues from its taxonomy[2].

[1] https://developer.foursquare.com/docs/api/venues/search
[2] https://developer.foursquare.com/docs/resources/categories

3.2 Characterizing Cities Based on Venue Data

We collected a data set of 5,723,169 venues in 180 cities around the world. Foursquare organizes its venues in a tree of 10 top-level categories, however, we only analyzed the ones relevant for characterizing the cities for travelers: *Arts & Entertainment*, *Food*, *Nightlife*, and *Outdoors & Recreation*. We intend to conceptualize these features as a multidimensional vector space model and represent each city as a point in this space. The characterization should approximate the expected experience that a tourist will have at a city.

To determine a city's score for a feature, we analyzed the distribution of the venue categories. Using the distribution instead of the absolute number of venues per category, we eliminated the effect of city size on the category features. Thus, we obtained the ratio of each feature in the city's category distribution by dividing the number of venues per each top level category by the total number of venues in that city. The underlying assumption is that these percentages are indicators of the association level of the city with the feature. This requires the cities to be of at least a certain size as the distribution of small cities is less reliable. Thus, the smallest city considered had at least 1,000 venues, with the median being 7,137. We did not analyze the quality of the venues, i.e., through ratings, as we expected having differences in the assessment of the quality owing to cultural differences.

Characterizing the cities according to their attractions is a first step; however, further features are of the travelers' interest. Using Climate-Data.org[3], we characterized each city using the mean yearly temperature and the mean yearly precipitation. Furthermore, we used Numbeo's "Cost of Living Index"[4], which is a relative cost indicator calculated by combining metrics like consumer goods prices, restaurants, transportation, and so on as an approximate price level of visiting the city. Finally, to account for the city size, we also used the number of venues as a proxy feature for the size of the city. Table 1 shows the raw values of the features.

3.3 Cluster Analysis

To evaluate the characterization of the 180 cities, we performed a cluster analysis, an unsupervised learning method whose goal is to group data items in a way that within the same group, the items are similar to each other, whereas the groups are dissimilar. Because the features of the destinations that we considered have different value ranges, we first applied min-max scaling to give each feature the same weight. To find the best segmentation, we experimented with common clustering algorithms, such as k-means, k-medoids, and hierarchical clustering. To evaluate the quality of the resulting clusters, we looked into metrics like the within-cluster sums of squares and the average silhouette width [30]. The former

[3] https://en.climate-data.org
[4] https://www.numbeo.com/cost-of-living/rankings.jsp

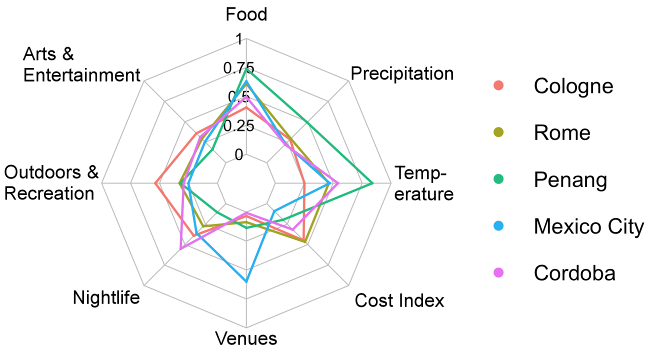

Figure 1: Normalized values of selected destinations

is a measure of the variability of the instances within each cluster, whereas the latter is a measure of how well the instances fit into their assigned cluster, as opposed to all the other clusters.

Using a systematic approach, we obtained the best results using hierarchical clustering and five clusters. The clusters named after the city closest to the centroid are "Cologne, Germany," with 74 Central European and North American cities; "Rome, Italy" with 35 cities in the Mediterranean and Oceania; "Penang, Malaysia" with 48 destinations residing mostly in Asia; "Mexico City, Mexico" with five metropoleis all around the world; and "Cordoba, Spain," with 18 small and relatively warm cities in different continents. Figure 1 shows the normalized values of the five characteristic cities.

4 A DATA-DRIVEN CONVERSATIONAL DESTINATION RECOMMENDER SYSTEM

Having characterized the destinations on eight dimensions, we facilitate it in a content-based critiquing recommender system. CityRec is implemented as a web application using NodeJS[5] and ReactJS[6] in the frontend. The codebase comprises about 3,500 lines of code and is available on Github[7]. A demo can be viewed at http://cityrec.cm.in.tum.de.

4.1 User Interaction with CityRec

The recommender system has three steps: (1) initial preference elicitation, shown in Figure 2 (a); (2) refinement through critiquing, shown in Figure 2 (b); and (3) a results page. In Step (1), we obtain the initial scores for the user profile by asking the user to select the destinations that best reflect her preferences from a set of 12 cities. We then construct an initial user model by averaging the feature values of the selected cities. This initial seed of 12 destinations is not random, but a diverse representation of the data set. We fill in the first nine slots by selecting two cities from each of the five previously established destination clusters (one in the case of the small "Mexico City" cluster). The remaining three slots are randomly selected cities to account for the size differences of the clusters. Using this approach, we can generate numerous, diverse, but equivalent shortlists because each cluster is represented. From these 12 cities, the users may choose three to five that best reflect their preferences. If a user does not recognize many cities, she can request another set of cities. Furthermore, a tooltip encourages the user to select cities that she finds generally interesting, including those she has already visited. This ensures that the system has enough data to work with for generating the initial user profile but avoids cases where users select many displayed cities, which end up in generic profiles with averaged-out feature values. The result of this step is an initial profile of the user that resides in the same vector space as the items.

In Step (2), we display a set of four initial destinations, computed using the Euclidean Distance. To give the users more control over their preference profile, we ask them to provide feedback on the initial recommendations by critiquing the cities' features one after another on a five-point Likert Scale: *"much lower" – "lower" — "just right" — "higher" — "much higher."* As can be seen in Figure 2 (b), the user now has more information about the cities, which establishes transparency and enables her to more informed decisions compared to in the first step. Using this feedback, we statically update the user profile scores by -0.2, -0.1, 0, 0.1, or 0.2 to attain a more refined preference model for the user.

Finally, in the last step, Step (3), the user is presented with a results page that shows a ranked list of the top five recommendations and their attributes, which can be explored. This page also contains the questionnaire for the evaluation.

4.2 Experimental Setup

The independent variable of the experiment is the version of the recommender system. Because we wanted to investigate the potential advantages and drawbacks of using critiquing in this domain, we created a baseline system in addition to the previously described critiquing-based recommender. The only difference in the baseline system was that the critiquing step, Step (2), is entirely skipped; that is, the outcome of the initial preference elicitation of Step (1) is the final result and is displayed in the same way as in Step (3).

The dependent variables are the usage metrics, such as the choices made at each step, the time taken to specify the preferences, and the number of clicks. Furthermore, we asked the user to fill out a subset of the ResQue Questionnaire, a validated, user-centric evaluation framework for recommender systems [28].

- (Q1) The travel destinations recommended to me by CityRec matched my interests
- (Q2) The recommender system helped me discover new travel destinations
- (Q3) I understood why the travel destinations were recommended to me
- (Q4) I found it easy to tell the system what my preferences are
- (Q5) I found it easy to modify my taste profile in this recommender system
- (Q6) The layout and labels of the recommender interface are adequate
- (Q7) Overall, I am satisfied with this recommender system
- (Q8) I would use this recommender system again, when looking for travel destinations

4.3 Results

A total of 104 individuals participated in the online survey from December 2018 to March 2019. Participants (44% females, 56% males)

[5] https://nodejs.org/en/
[6] https://reactjs.org/
[7] https://github.com/divino5/cityrec-prototype

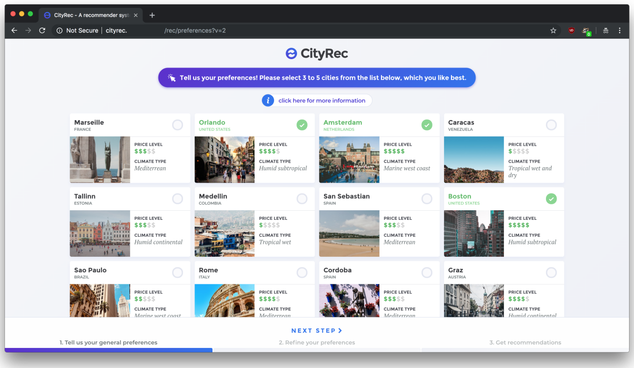

Figure 2 (a): Selection of favorable cities, Step (1)

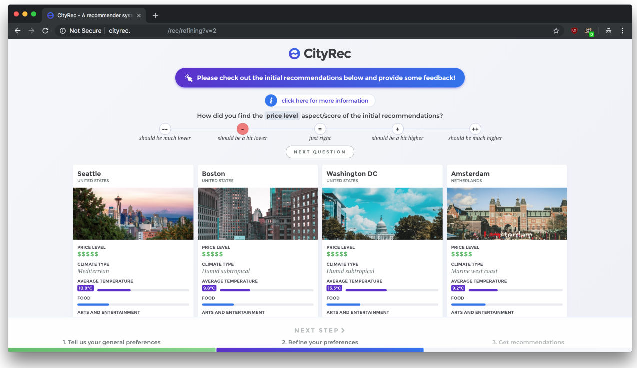

Figure 2 (b): Critiquing of initial recommendations, Step (2)

were recruited by sharing the user study on social media and among groups of friends and colleagues. The self-reported ages were 0–20 (7%), 21–30 (69%,) 31–40 (9%), and 41–50 (5%). Random assignment of the systems was performed after a landing page and had almost equal (51% versus 49%) completion of the survey.

Table 2: Differences between the two systems

Variable	Basel.	Critiqu.	p	W	Sig.
(Q1) Interest match	3.58	**3.88**	**0.043**	645	$*$
(Q2) Novelty	3.44	3.75	0.118	705	ns
(Q3) Understanding	3.46	3.77	0.073	673.5	ns
(Q4) Tell prefs.	3.73	3.90	0.328	775	ns
(Q5) Modify profile	3.24	3.48	0.17	723.5	ns
(Q6) Interface	**4.15**	3.62	**0.009**	1,044	$**$
(Q7) Satisfaction	3.66	**3.92**	**0.037**	649	$*$
(Q8) Future use	3.49	3.67	0.166	724	ns
Time to results	60.92s	**184.07s**	**<0.001**		$***$
Clicks	6.32	**21.35**	**<0.001**		$***$
PCC Food	-0.11	-0.01	0.341		ns
PCC Arts	0.05	0.38	0.066		ns
PCC Outdoors	0.02	**0.45**	**0.024**		$*$
PCC Nightlife	0.2	**0.57**	**0.028**		$*$

Significance levels: $*\, p < 0.05$; $**\, p < 0.01$; $***\, p < 0.001$

The upper part of Table 2 shows the differences in the mean values and the significance tests of the dependent variables. The mean values of the ordinal answers to the questionnaire (Q1–Q8) are for viewing purposes only; the test statistic was calculated using the Wilcoxon rank sum test with continuity correction for independent populations. The null hypotheses were that the medians of variables of the two groups are equal. In three cases, (Q1), (Q6), and (Q7), we could refute the null hypothesis, which provides interesting insights into the users' assessment of the system.

In the survey, we also asked the participants to rate their personal importance of tourism-related aspects. Thus, we could compute the Pearson Correlation Coefficient (PCC) between the actual profile from the system and the self-assessment from the survey. The lower part of Table 2 shows these correlations per system and the result of the one-sided Fisher's r-to-Z test for independent samples.

4.4 Discussion

The significant difference in (Q1) shows that the perceived recommendation accuracy is higher, when using the proposed critiquing recommender system, however, at the cost of worse interface adequacy (Q6). This is attributable to the overhead of the critiquing step, Step (2), as it takes triple the time to complete the first two steps and more than triple the number of clicks. Interestingly, the users value higher accuracy more than the adequacy of the interface and the effort as can be seen in the significantly higher user satisfaction (Q7) and the similar levels of potential future use (Q8).

Furthermore, we observed that the user profiles of the critiquing system are significantly higher correlated with the self-assessment in the case of Outdoors & Recreation and Nightlife. This is further evidence that the critiquing recommender version performs better in capturing the preferences of the user. In conclusion, the critiquing version should be preferred as it provides better recommendations from the users' perspective.

5 CONCLUSIONS

In this paper, we proposed an approach for tackling the problem of recommending complex items in the domain of travel recommendation. We characterized destinations around the globe in a user-understandable way and directly used this characterization in an online recommender system. From the evaluation experiments conducted, we discovered an interesting trade-off between the perceived recommendation accuracy and the perceived adequacy of the user interface; however, the users seemed to favor better recommendations over less effort to obtain them.

Because CityRec's source code has been released, it can also serve as a foundation for the community to investigate conversational recommender systems based on data-driven item characterization. The destination characterization showed decent results; however, it would be worthwhile to investigate further useful features of destinations that can be derived from other data sources. In this study, we found that, despite higher perceived accuracy (Q1), the interface adequacy (Q6) was rated lower in the critiquing system. Thus, we regard this study as a first step that is to be extended with a more sophisticated preference elicitation approach using active learning. Furthermore, the behavior of the algorithm, with respect to the diversity of the recommendations, should be analyzed as well.

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